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Our methodology models joint military performance and examines capabilities associated with combining systems. Evaluation of tactics, techniques and procedures, measures of performance, and measures of outcome is common within the Department of Defense; developing an over-arching predictive tool is desired. Trade space analysis, response surface methodology, and optimization are not new approaches; the combination of these into an orchestrated process is.

A variety of capabilities each with a range of performance values combine to produce results in an area. A specific capability determines the end state resulting of combination; the desired end states may differ from campaign to campaign. All possible combinations of contributing systems describe the capability.

An optimization process explores the performance parameters for all systems simultaneously, aggregates system values to define capabilities, and searches for the optimal combination of capabilities. The optimization process is provided response surface approximations over which to search for optimal regions.

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Warfare Integration Techniques Exploring Trade Space Among Joint Military Capabilities

WARFARE CAPABILITY INTEGRATION

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July 2003

JOINT WARFARE ANALYSIS DEPARTMENT

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1 PROJECT OVERVIEW

1.1 STUDY OBJECTIVE

Developing an optimization technique that uses system performance data to explore multi-dimensional trade spaces among military capabilities is beneficial to military sponsors. This study develops an understanding of trade space among military platforms and their combined contribution to warfare capability. This understanding is to be exploited by the use of response surfaces that map configured output from military models (simulation based or not) into multidimensional space. Once mapped, the response surface yields useful comparisons of platform contributions toward capabilities supporting military campaigns. Ultimately, the goal is to integrate multi-dimensional trade spaces into a common analytical picture representing a warfare area. Overall, this work is a proof of concept the goal of which is to develop a tool with analytic rigor to integrate military capabilities defining warfare areas.

1.1.1 Integration

Military analysis focuses on warfare from various perspectives and at different echelons. It is critical to take an integrated perspective of joint assets as warfare areas generally separated by air–land–sea become more closely associated and merge for combined effect on the battlefield. The joint commander must make "all arms" decisions that optimize the use of joint, even international, assets. Military sponsors are interested in analysis that directly addresses interactions at the capability level. These are the interactions of platforms but with a decided focus on the overall effect or synergy associated with a particular combat mix. The study plan depicted in Figure 1.1 was used to develop a methodology by gathering data representative of military conflict on a large scale, developing mathematical approximations of the response variables, and optimizing across these approximations to derive the most beneficial combination of assets to achieve the desired outcome.

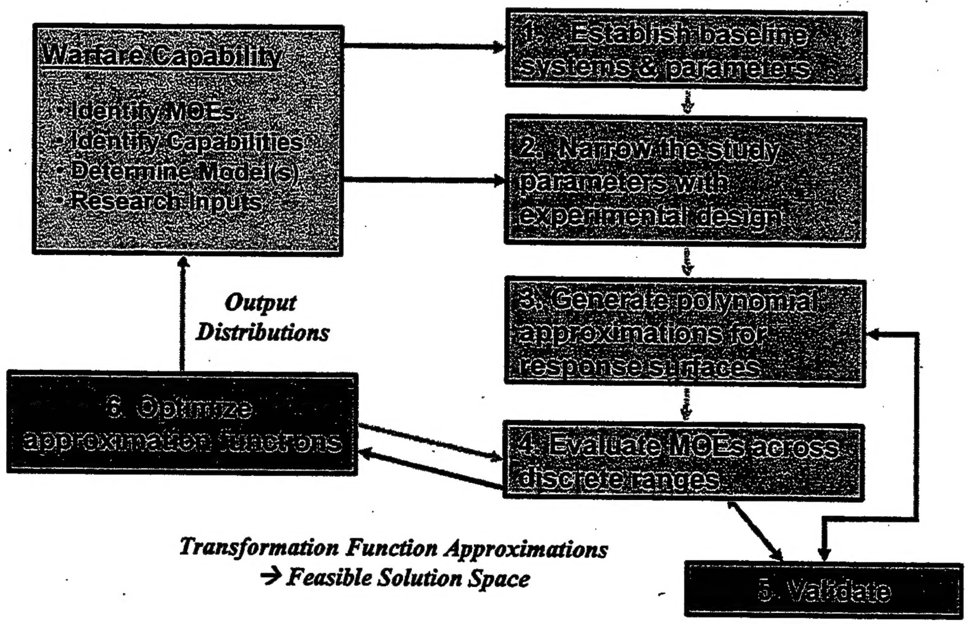

Figure 1.1. Structure of the research plan.

1.1.2 Analysis

Response surface methodology (RSM) is a predictive model that forecasts performance. We approximated this multi-dimensional surface by evaluating tactics, techniques, and procedures while observing their effect via measures of effectiveness (MOE). This surface approximates the entire feasible space. The military commander can further constrain a scenario/campaign or region of interest to a specific portion of the surface. Within this region, the commander will understand the marginal value of platforms, tactics, and objectives. These may be weighed against each other or traded to produce a range of desirable outcomes.

Step 1 (Model Selection and Data Configuration)

. The Joint Integrated Contingency Model (JICM) was used to develop data for analysis. Input parameters were selected and configured on the basis of their significance of their effect and commonality across platforms.

Step 2 (RSM Configuration/Trade Space Development)

Experimental design is used to develop a complete picture of the simulation output. Data analysis produces polynomial approximations of these responses creating response surfaces. We used second-order approximations although higher-order predictors could be produced.

Step 3 (Trade Space Integration)

The surface approximations are combined and analyzed, producing comparisons between effects associated with all joint assets contributing to the capability. An

optimization tool was developed that considers the response surfaces associated with every measure of outcome.

Step 4 (Capability Assessment)

The end result is rapid assessment across scenarios including analytic excursions exploring various campaign options, and these excursion results can be produced in minutes.

1.1.3 Joint Sponsors

This type of analysis is being conducted throughout the Department of Defense. The U.S. Army is performing "Value Added Analysis" to evaluate their modernization plan at the Center for Army Analysis, Ft. Belvoir, VA.[1] The US Air Force's Air Combat Command is analyzing effects-based modernization at Langley Air Force Base, VA.[2] The U.S. Navy Pacific Command and Air Force Center for Studies and Analysis has voiced interest in this type of process.

1.2 CONCEPT OF WARFARE INTEGRATION

1.2.1 Background

Extensive applications of RSM are seen in the industrial world, particularly in situations where several input variables potentially influence some performance measure or quality characteristic of a process. This performance measure or quality characteristic is called the response. It is typically measured on a continuous scale, although attribute responses, ranks, and sensory responses are not unusual.[3] RSM is a collection of tools for understanding the nature of a relationship between independent variables and some measure of performance. The three key elements of RSM are design of experiments, empirical modeling, and optimization. The input variables are considered independent and are controlled by the investigator. Statistical and mathematical modeling is used to develop an approximate relationship between a response variable (Z) and input variables ($\xi_1, \xi_2, \ldots \xi_k$). Optimization methods are used for finding levels of the input variables that produce the desired value of the response. Modeling curvature is very important when the objective is to find an optimum response.[3] The functional form is

$$Z = f(\xi_1, \xi_2, \ldots \xi_k) + \varepsilon,$$

where ε represents sources of variability not accounted for in the function; this can be measurement error and background noise. The investigator assumes that there is a mathematical relationship between the variables, but the specific relationship is unknown. Usually a lower-order polynomial in a region of the independent variable space represents the response as a surface in space.

If the fitted surface is an adequate approximation of the true response, then analysis of the fitted surface is equivalent to analysis of the actual system. This allows the investigator to estimate the response using the surface rather than conducting additional, costly, time-consuming experiments. The investigator simply reads the response from the graph.

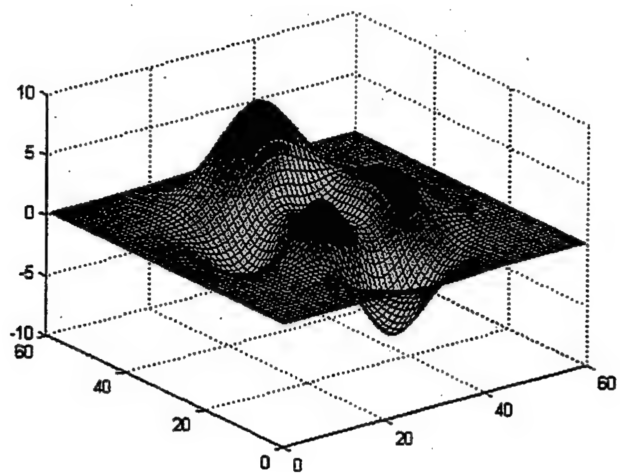

Figure 1.3. Example response surface. The vertical axis is a predicted result of combining the two horizontal variables.

1.2.2 Experimental Design Applied to Warfare Integration

Joint warfare involves many combat platforms with associated command and control equipment. The argument between aggregate and disaggregate representation has significant impact on the use of this research and this methodology. The approach here is a fairly standard representation of combat platforms as systems-of-systems where each major system is composed of a list of minor systems contributing to its performance. A computer model generates simulated combat results representing the major systems performance recorded as measures of outcome (MOO). Figure 1.4 represents the conceptual data development. A matrix of major systems [*S*] is established, and each major system is defined by the value of its sub-systems [Val]. This *S* matrix is provided to a computer model that transforms the input matrix into simulated combat results and records specified measures of outcome into a matrix [*M*]. Ultimately, the starting conditions for the systems can be compared graphically to the MOO using a response surface. The major systems are the factors for the experiment because they are established by the investigator.

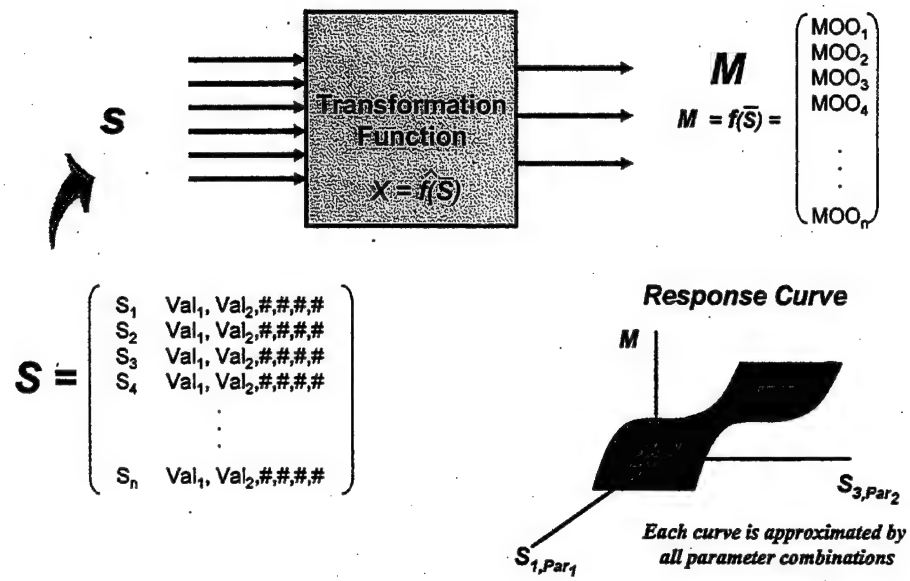

Figure 1.4. The transformation of matrix input into a response matrix.[4]

Discussed here briefly are the mathematics behind this process, where each major system S_k is represented by ξ_k. The factors ξ_1, ξ_2, ... ξ_k are called natural variables. They represent the natural units of measure (e.g., when measuring velocity, the value of ξ_1 may be 60 miles/hour [mph]). It is better to use coded variables $X_1, X_2, \ldots X_k$ of the form

$$X_{ij} = \frac{\xi_{ij} - \dfrac{\max(\xi_{ij}) + \min(\xi_{ij})}{2}}{\dfrac{\max(\xi_{ij}) - \min(\xi_{ij})}{2}}.$$

The distribution of values for each variable is "normalized" to fall between −1 and 1 with mean zero and have the same standard deviation as ξ. Fundamental to choosing a design that minimizes estimation variance in the response is that values are also orthogonal. Varying only one factor at a time can establish knowledge of the effect of one factor when the others are held constant.

It is desirable to measure interactions between variables. Interaction implies that the effect of one factor on the response does not remain the same for different levels of a second factor. To obtain information on interactions, the levels of each factor are varied and all possible combinations are considered; this is called a *factorial experiment*. The value of a factorial experiment is that it looks at several factors simultaneously and allows various effects to be estimated, thus allowing the investigator to draw conclusions over a wider range of conditions.

One disadvantage of factorial experiments is that the number of treatment combinations increases rapidly as the number of factors and/or levels increases. Three variables examined at two levels may be easily considered at every possible combination ($2^3 = 8$) while ten variables at two levels exponentially increases the requirement ($2^{10} = 1024$). One method is to consider only a subset of all possible treatment combinations, a *fractional factorial*. Factorial designs collect data at the vertices of a polyhedron in *p*-dimensions (*p* is the number of factors being studied). Fractional factorial designs collect data from a specific subset of all possible vertices. It is reasonable to assume that most systems are largely affected by main effects and low-order interactions. This "sparsity of effects principle" is the underlying assumption that higher-order interactions are usually unimportant when the experiment is considered as a whole. Thus, by selecting the proper combinations, the investigator can determine how two or three factors interact but sacrifices the ability to determine higher-order interactions.[5]

2 SIMULATING JOINT WARFARE CAPABILITY

2.1 ESTABLISHING THE ENVIRONMENT

2.1.1 Overall Campaign

A campaign scenario was established in order to exercise a wide variety of military platforms in diverse environments and situations. Two theaters were selected: Northeast Asia (NEA) and Southwest Asia (SWA). Existing NEA and SWA scenarios were modified to minimize development time. The selection of these two theaters provided several experimental and analytical advantages: (1) The diversity of terrain and weather required the military equipment to operate across a wider range of capabilities; (2) the opposition forces are very different in their composition, tactics, and equipment; and (3) databases containing these theaters exist and have been validated.

Joint Forces

The basic structure of U.S. and Allied forces in each of these theaters was kept the same. The "real-world" strength of forces was modified in an effort to produce larger variance in their interactions and gauge overwhelming, as well as unsatisfactory, power projection. The combat plans focused on maintaining consistency of the experimental design in order to minimize spurious variation in outcomes. Thus, even when additional air or combat power was available in the theater, the concept of operation and scheme of maneuver remained the same.

Threat Force Representation

In each case, the opposition forces were to invade the neighboring country. The United States and Allies were to conduct a "Halt Operation" to deny the objective and stop the enemy advance.

2.1.2 Analysis Focused on Two Theaters

SWA Theater

The SWA theater concept is shown in Figure 2.1.

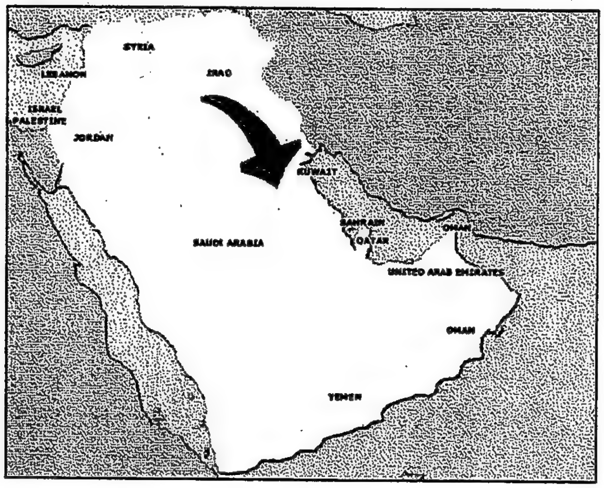

Figure 2.1. The SWA theater concept.

The key to Iraqi success in this scenario is a rapid ground advance that would allow forces to threaten the port at AdDammam and force the U.S. forces to adopt a different operational plan rather than reinforce through that port. For simplicity we did not simulate the deployment of U.S. forces to the theater but assumed that they were in place on D-Day. Since only the halt phase was simulated, this assumption is not unreasonable.

SWA Ground Force Structure

In order to minimize the warning to Blue, Iraq used only nine divisions out of the entire ground force for the attacks in this scenario. The Blue defense consists of eight heavy brigades of the Gulf Cooperation Council (GCC) and the U.S. brigade of varying capability depending on the case (Table 2.1). In the medium case, the U.S. brigade consisted of 200 tanks, 200 Infantry Fighting Vehicles (IFV), 200 armored personnel carriers (APC), and, 200 heavy armored vehicles in the armor category. The infantry consisted of 140 short-range anti-armor missiles and 1666 small arms. The artillery category was represented by 100 self-propelled artillery pieces. Changing the armor, infantry, or artillery variable to the low setting cut these numbers in half while the high setting increased them by 50%.

Table 2.1. SWA ground summary.[6]

- Iraq
  - 9 heavy divisions (6 Armor, 3 Mech)
- GCC
  - 8 heavy brigades (4 Armor, 4 Mech)
- US
  - 1 Brigade varying in Armor, Inf, and Arty
  - 1, 2, or 3 Patriot Bn (3 Patriot II, 1 Patriot III each)
  - 1, 2, or 3 Aviation Bn (20 Apache-D each)

In addition, the number of U.S. Patriot and aviation units (attack helicopters) varies with case. The Patriot battalions have six Patriot II launchers and two Patriot III launchers. There are 20 Apache helicopters in each battalion, and the low, medium, and high levels of this variable meant that either one, two, or three battalions were sent.

SWA Air Force Structure

The Iraqi air force is about a 50/50 mix of modern and older-generation fighter aircraft (Table 2.2). Pilot proficiency is relatively low, however, so overall performance is modest, particularly in the air-to-ground role.

The GCC air force consists of relatively modern aircraft. Pilot proficiency, especially in the air-to-ground role, is well below U.S. standards.

Table 2.2. SWA air summary.[6]

- Iraq
  - 325 fighters
- GCC
  - 484 fighters
- US
  - 63, 126, or 189 fighters (USAF)
  - 40 bombers
  - 54, 108, or 162 fighters (USN)

The U.S. aircraft deployment consists of 40 heavy and medium bombers and a variable number of U.S. Air Force (USAF) and U.S. Navy (USN) fighter aircraft. These deployments mirror the 50% of the medium value for the low case and 150% of the medium value for the high case as was seen for the U.S. ground deployments. Note that some U.S. Navy aircraft, even in this relatively low threat environment, must be employed for fleet air defense rather than offensive missions in the theater.

NEA Theater

The success of a North Korean attack depends on forcing a political settlement before the United States can bring reinforcements to bear to reverse any Red gains. Thus, as in the NEA scenario, there is a premium on rapid early success. The SEA theater concept is shown in Figure 2.2.

Figure 2.2. The NEA theater concept.

NEA Ground Force Structure

Unlike the SWA scenario, the deployed U.S. brigade has only a supporting role in the halt. The U.S. aviation, both fixed and rotary wing, and to a lesser extent the air defense will affect the halt conditions in the simulation.

While attempting to achieve some degree of surprise and hence rapid success, North Korea does not mobilize its entire army but attacks with a subset of ground forces. For the halt phase of this rapid response scenario, South Korea defends with available active duty forces. Reserve forces might play a role in later phases of the combat but only the halt phase was simulated so those forces had no role in this simulation. The U.S. forces mirror those used in the SWA case (Table 2.3).

Table 2.3. NEA ground summary.[6]

- North Korea for each of 3 axes
  - 1st echelon, ID, IB, ArtyB, and 2 MRLB
  - 2nd echelon, ArmB, MXB, MRLB, ArtB
  - 3rd echelon, MXB, ArtB
- South Korea for each of 3 axes
  - 2 ID, MRD, MXD, 2 ArtB, FAG
- US
  - 1 Brigade varying in Armor, Inf, and Arty
  - 1, 2, or 3 Patriot Bn (3 Patriot II, 1 Patriot III each)
  - 1, 2, or 3 Aviation Bn (20 Apache-D each)

NEA Air Force Structure

The North Korean air force, while numerically significant, consists largely of older-generation aircraft. North Korean pilots get relatively few flying hours for training, so proficiency is marginal.

The South Korean air force represents a mix of older-generation and more modern aircraft. Pilot proficiency is much better than that of their North Korean counterparts.

As in SWA, the U.S. aircraft deployments consist of 40 heavy and medium bombers and a variable number of fighter aircraft (Table 2.4).

Table 2.4. NEA air summary.[6]

- North Korea
  - 780 fighters
- South Korea
  - 353 fighters
- US
  - 40 bombers
  - 63, 126, or 189 fighters (USAF)
  - 54, 108, or 162 fighters (USN)

2.2 SIMULATION SELECTION

2.2.1 Criteria

The criteria for simulation selection were straightforward: (1) The simulation must represent joint U.S. military operations; (2) it must be affordable to acquire and use; and (3) it must run quickly in order to simulate multiple iterations of the campaign. In addition, it was desirable for the simulation to be available to JHU/APL for future use, be

validated/accredited by the Department of Defense, and have some pedigree of use among military analysts.

2.2.2 The Joint Integrated Contingency Model

The JICM is a global analysis and war-gaming system developed at RAND under the sponsorship of the Director of Net Assessment in the Office of the Secretary of Defense. It encompasses the strategic and operational levels of land, air, and sea warfare with a global set of models and databases. JICM is a deterministic model with a minimum 4-hour time step. Brigade- and division-sized ground units are organized into corps-level commands that maneuver on a predefined network with variable terrain type and width. The NEA movement network is shown in Figure 2.3. Air combat is organized around an air tasking order that packages sorties at the beginning of the day to execute across the designated time periods. Maneuver combat is adjudicated by totaling weapon scores and calculating loss rates and movement from force ratios.[9]

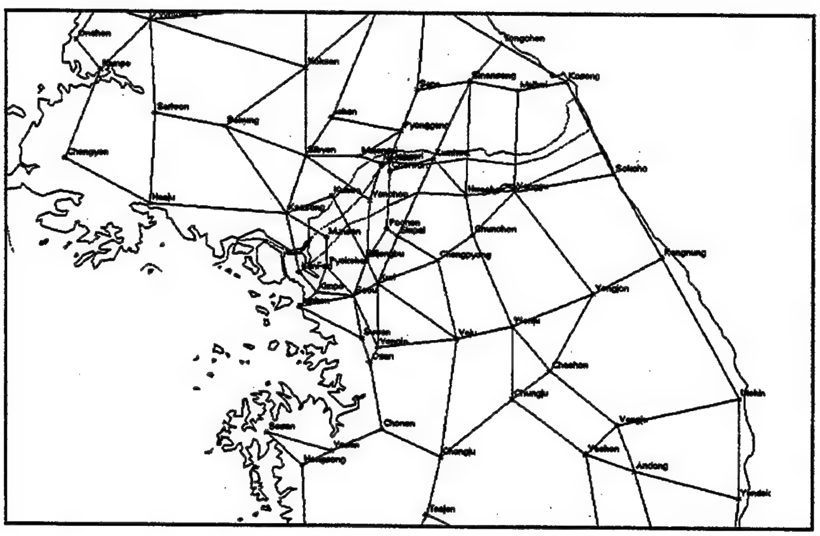

Figure 2.3. JICM ground model movement network.[9]

2.3 EXPERIMENTAL DESIGN

2.3.1 Establishing the Input Parameters

In this research we want to approximate a quadratic model for 13 coded input variables and 28 response variables. Table 2.5 lists the 13 variables with their associated natural and coded levels.

Table 2.5. Values for varying parameters.

Input Variables	Description	Natural (ξ)	Natural Levels	Coded (x)	Coded Levels
MR	Red Advance Rate multiplier	ξ_1	1, 2, 3	X_1	–1, 0, 1
SCUD	Scud effectiveness against airbases multiplier	ξ_2	1, 2, 3	X_2	–1, 0, 1
PAT	U.S. air/missile defense battalions Patriot I and Patriot III	ξ_3	3, 6, 9 1, 2, 3	X_3	–1, 0, 1
ARM	U.S. IFV, APC, and armor per brigade	ξ_4	100, 200, 300 100, 200, 300 100, 200, 300	X_4	–1, 0, 1
INF	U.S. anti-armor and small arms per brigade	ξ_5	70, 140, 210 833, 1666, 2500	X_5	–1, 0, 1
ARTY	U.S. self-propelled artillery per brigade	ξ_6	50, 100, 150	X_6	–1, 0, 1
HELO	U.S. attack helicopters per brigade	ξ_7	20, 40, 60	X_7	–1, 0, 1
TLAM	U.S. TLAM used to attack airbases	ξ_8	200, 400, 600	X_8	–1, 0, 1
JSOW	U.S. Precision Guided Munitions quantity	ξ_9	**	X_9	–1, 0, 1
ATCM	U.S. ATACM quantity	ξ_{10}	30, 60, 90	X_{10}	–1, 0, 1
USAF	USAF fighter/bomber aircraft deployed	ξ_{11}	103, 166, 229	X_{11}	–1, 0, 1
NAVY	USN carrier battle groups deployed	ξ_{12}	1, 2, 3	X_{12}	–1, 0, 1
RSAM	Red replacement days for SAM available	ξ_{13}	0, 2, 4	X_{13}	–1, 0, 1

Various precision guided munitions were represented collectively by the Joint Standoff Weapon (JSOW) variable. The munitions quantity (shown by ** in Table 2.5) and their nominal values are as follows:

5300	JDAM1
1800	JDAM2
800	JSOWC
800	JSOWS
8800	WCMDC
1200	WCMDS
2100	HARM

The medium level for NAVY is two carrier battle groups (CVBG) operating in each theater. The nominal CVBG will carry 12 F-14 and 36 F-18C/E. The nominal USAF deployment is listed below. It includes tankers, an Airborne Warning and Control System (AWACS), and a Joint Surveillance Target Attack Radar System (JSTARS) (not explicitly played):

18	F-15C (air-air)
24	F-15E (multi)
36	F-16 block 50 (HARM shooters for SEAD)
12	A-10
36	F-16 block 40 (LANTIRN capable)
Plus:	
8	B-2
10	B-1
10	B-52
12	F-117

2.3.2 Minimizing Run Time

We are interested in a second-order polynomial of the form

$$y = \beta_0 + \beta_1 x_1 + \ldots + \beta_{13} x_{13} + \beta_{14} x^2_1 + \ldots + \beta_{26} x^2_{13} + \beta_{27} x_1 x_2 + \ldots + \beta_{104} x_{12} x_{13},$$

where each variable is considered at three levels. At least 105 design points are required to estimate the coefficients using least squares. For 13 variables at three levels each, a full factorial experiment would consist of $3^{13} = 1{,}594{,}323$ simulation runs by the JICM. This is definitely a case for fractional factorial design. Fractional factorial design procedures developed by JHU/APL allow a significant reduction in design runs to capture these effects.[10] A design can be created that estimates all of the first- and second-order effects with 729 runs. Of the approximately 1.5 million possibilities, only 879 cases were run (729 for experimental design and 150 for validation).

2.3.3 Measures of Outcome

Twenty four (24) measures of outcome per theater were collected and are listed in Table 2.7.

Table 2.7. Complete listing of MOO.

Halt % area	USN AC start
Halt time (to 1/2 day)	USN AC loss to AA
Red AC start	USN AC loss to SAM
Red AC loss to AA	USN AC loss to all other
Red AC loss to SAM	US Ground ED start
Red AC loss to all other	US Ground ED loss
Red Ground ED start	USAF AC start
Red Ground ED loss	USAF AC loss to AA
Ally AC start	USAF AC loss to SAM
Ally AC loss	USAF AC loss to all other
Ally Ground ED start	Effective Divisions
Ally Ground ED loss	Effective Division Attrited

2.3.4 Stopping Conditions

The halt phase ends when one of three criteria is met: (1) Red reaches objective positions (Red win); (2) Red is attritted down to 40% (Red loss); or (3) time expires at 15 days (Red loss by not achieving its objective). Each iteration of the simulation continued until one of the stopping conditions was met.

There were several choices for stopping conditions not used. Letting all battles run through either the defeat or success of Red forces is a reasonable condition but, under many of the 729 starting conditions, Red and Blue reach a stalemate that continues for months; such battles are a poor comparison to those that last only hours.

2.4 SIMULATION RESULTS

2.4.1 Collected Data Viability

The theaters considered are very compact. In both, Red forces advance along a single corridor and pursue a limited objective. No consideration was given to the total force structure of the Department of Defense; only assets in the theater were used, with no possibility of replenishment or reinforcement no matter how long the battle lasted.

The JICM does not model naval battles at sea and represents land forces as brigade-sized units. This limited the scope of modeling done for this study by reducing the fidelity available.

2.4.2 Verification

A verification process was established for the JICM output data. Output was examined graphically and through subject matter expert (SME) review for divergence from accepted norms. This procedure for verification is acceptable because the output is expected to conform to standard military accepted practices—the expected value outcome is desired. MOO dependency on input parameters was examined as well as the general behavior of significant factors for each approximation.

3 DEVELOPING RESPONSE SURFACES

3.1 APPROXIMATING THE SURFACE

3.1.1 Measures of Outcome Explained

The significant factors for the primary MOO (Halt Max %) are shown in Figure 3.1. For NEA, a total of nine factors are in the response surface model, with eight significant at the 0.01% level (shown in purple). There are 10 significant interactions among the factors listed. For SWA, a total of nine factors are in the response surface model, with six significant at the 0.01% level (shown in purple). There are 14 significant interactions among the factors listed in Figure 3.1.[3] (See Appendix B for the significant interactions associated with the response approximations.) Figure 3.2 shows representative plots of interactions with strong influence and indicate factor behavior between the two most significant factors and the identified MOO. These plots are located in Appendix B for all of the other MOO.

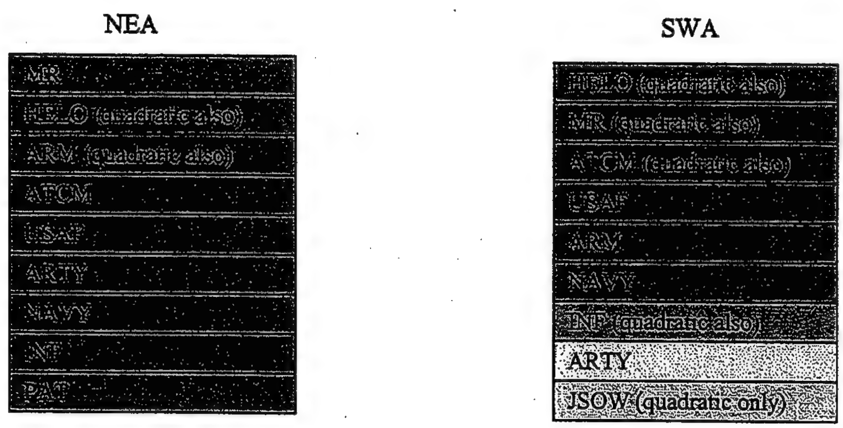

Figure 3.1. Significant factor displays.

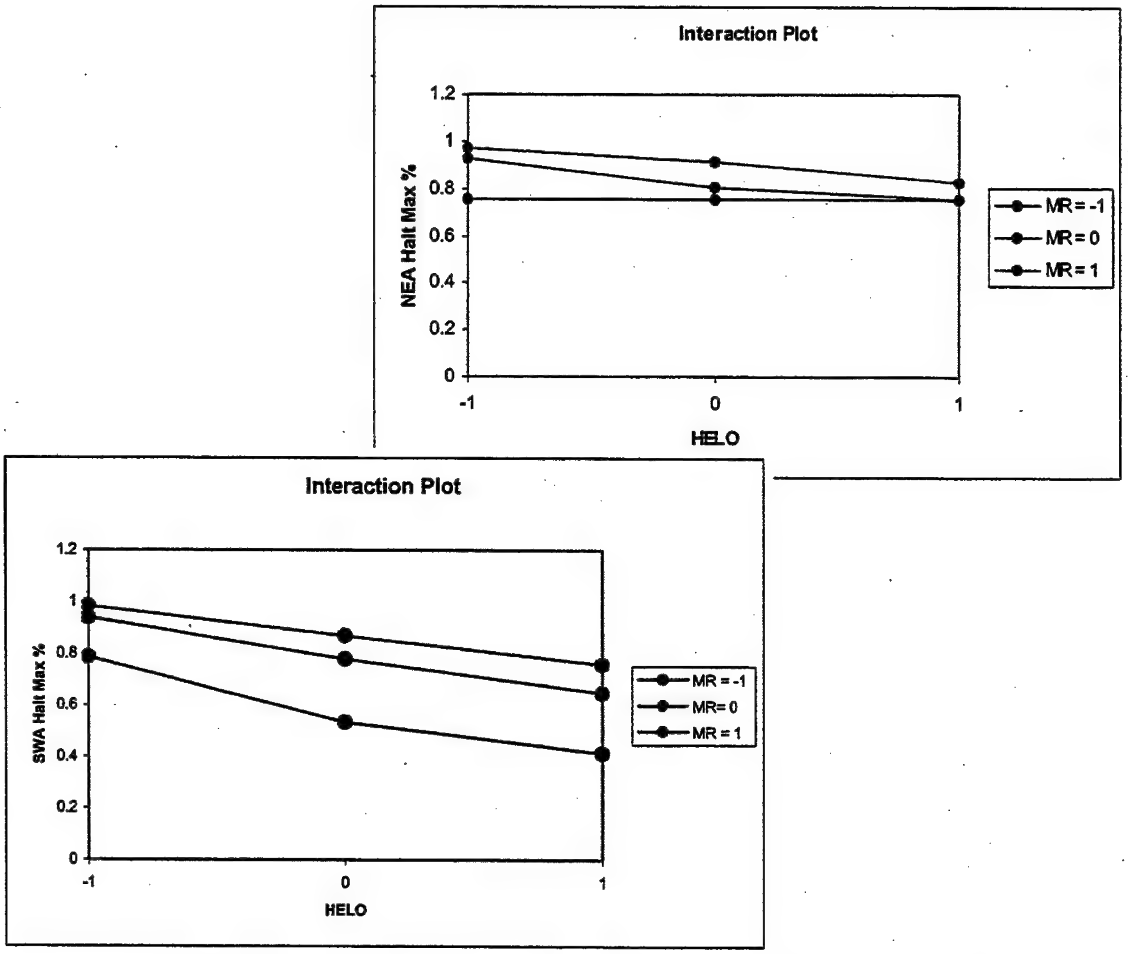

Figure 3.2. Plots for strong interaction: (upper) NEA; (lower) SWA.

3.1.2 Interpreting n-Space

The polynomials developed describe a polyhedron and specific vertices along its edge. This process hopes to move along the surface of each polyhedron and find maximum or minimum points. Because the surface is in multidimensional space, it is hard to visualize this search.

The experimental design matrix allowed a hyper-surface to be constructed. This surface looks more like a "net" than a solid sheet, however. Each of the 729 runs provided a new point of intersection or node for the strings of the net. The more runs, the more points of intersection, and the more solid the surface becomes. A significant drawback of this process is that the space between these nodes is unmodeled and the true behavior of the model in that region is unknown. This is not generally a problem when discrete input parameters are considered, but in this case many discrete, integer levels of each parameter exist between the minimum, middle, and maximum values. There is the possibility that the model is chaotic or non-monotonic in these intervals and that this behavior is undetected (i.e., the model will produce quadratic responses while the actual system varies wildly).

3.2 DATA ANALYSIS

3.2.1 Low-Dimension Surfaces

STATISTICA and MATLAB were used to show simple graphic relationships between the two most significant factors for each MOO. This was confidence building and allowed SMEs to make graphic comparisons to accepted or intuitive standards. Figure 3.3 shows one such plot relating Patriot missile batteries and Tomahawk missiles (TLAMs) to the number of Red aircraft lost because of surface-to-air missiles (SAMs). It is expected that as the number of TLAM increases there is little effect on air losses for the enemy. However, the Patriot batteries directly engage enemy aircraft in flight, and as their quantity increases there is a steep slope in the aircraft lost MOO. These types of comparisons were done for all MOOs as part of the verification process.

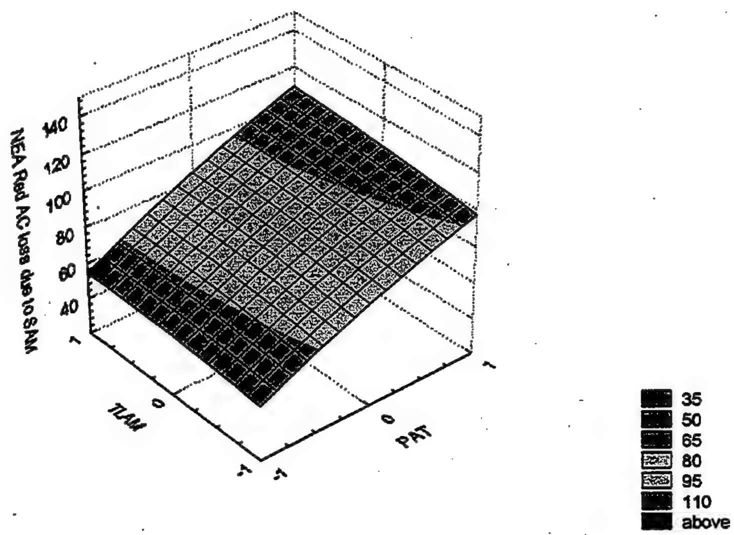

Figure 3.3. Patriot and TLAM, 2-D surface for "RED Aircraft Lost to SAM."[3]

3.2.2 Regression

It is always necessary to examine the fitted model to ensure that it gives an adequate approximation to the true system and that none of the least squares assumptions are violated. If this is not done before proceeding with the exploration and optimization of the fitted response surface, the model will likely give misleading results. Several regression methods are used to accomplish this, including variable selection techniques and prediction criteria. Often it is difficult to resist the temptation to make the model overly complicated; model selection does not necessarily mean perfect fit. The coefficient of determination, R^2, measures a model's capability to fit the data (i.e., how far away from the predicted value is an actual measurement expected to be?). The use of R^2 is risky because almost any addition of a new model term results in an increase in R^2. A system modeled by every possible parameter will provide perfect results but be very complex and not responsive to changes. A better criterion to use is the adjusted R^2

because it guards against overfitting. It punishes the user who includes marginally important model terms to gain accuracy.

One would also like to select a model that will best predict the response. Ordinary residuals are not generally indicative of how the regression model will predict as they are a measure of quality-of-fit and have no bearing on future prediction. A very important criterion, used as a form of model validation, is the PRESS statistic. The PRESS residual is a measure of prediction error:

$$\mathrm{PRESS}_{\mathrm{resid}} = e_{i,-i} = y_i - yhat_{i,-i}$$

The value $yhat_{i,-i}$ is the predicted response without observation i in the model. The data points where prediction is poor is a point where the PRESS residual is much larger in magnitude than the ordinary residual:

$$\mathrm{PRESS}_{\mathrm{stat}} = \sum\nolimits^{n}_{i=1}(e_{i,-i})^2.$$

Here y_i is not simultaneously used for fit and model assessment. For the choice of the best model, the user would want the smallest PRESS.

Another criterion, C_p, deals with model fit. A model that is too simple may have biased coefficients and prediction. An overly complicated model will result in large variances in the coefficient and in the prediction. We want to choose a proper subset of regressors so that a suitable balance between overfitting and underfitting is reached. The C_p statistic can be an extremely useful criterion for discriminating between models. One favors the candidate model with the smallest C_p value.

The C_p for a p regression model is

$$C_p = p + (s^2 - \sigma^2)(n - p)/\sigma^2.$$

Figure 3.4 gives examples of the statistics and how they relate to the MOO % Halt Max as discussed. It shows the MOO consisting of a number of parameters (p), MSE (mean square error), PRESS, Adj R^2, and C_p for models at each significance level. If a model contained a significant interaction, its main effects are included in the model, whether they were significant or not. The choice of polynomial approximations came by considering the criteria, significance level of the parameters, and the size of their coefficients.

Adj R^2	PRESS	C_p	MSE	p
78.4	1.57	18.03	.00212	14
79.5	1.49	16.57	.00202	17
79.9	1.47	15.86	.00198	18
80.4	1.44	17.91	.00193	22

Adj R^2	PRESS	C_p	MSE	p
93.1	1.86	26.01	.0025	18
93.3	1.82	25.22	.0024	20
93.4	1.79	25.05	.0024	21
93.5	1.78	26.24	.0024	23
93.6	1.74	27.34	.0023	27
93.9	1.70	31.11	.0022	33

Figure 3.4. Statistics for MOO Halt Max %.

3.2.3 Residuals

Once the approximations are derived for each measure of output, diagnostics help detect unusual points in the data set. Parameter estimates and predictions may depend more on an influential subset of the data than on the majority. We want to locate influential points and assess their impact on the model. Analysis of the residuals can be used to detect such things as model misspecification, departure from the homogeneous variance assumption, existence of suspect data points, and isolated high-influence data points. If there are "bad" values, they should be eliminated, but if there is nothing wrong with the points except that they control major model properties, we would like to know.

After running several procedures in SAS®, version 8.2, several statistics were examined to aid in detecting unusual data points. An outlier is a data point that is extreme in the vertical direction (see Figure 3.5). Detection of an outlier means that an observation does not agree with the specified model. A usual way to detect outliers is to see if any of the residuals are very large compared to the rest of the residuals. A common statistic, which accentuates outliers, used as a diagnostic in the detection of outliers is the *R*-Student statistic (t_i). An observation is considered an outlier if its *R*-Student value was greater than 3.92 roughly. Table 3.1 lists extreme observations that are considered outliers; if an MOO does not have any outliers, it is not listed. High-influence points are characterized by data points that are extreme in both the x and the y direction.

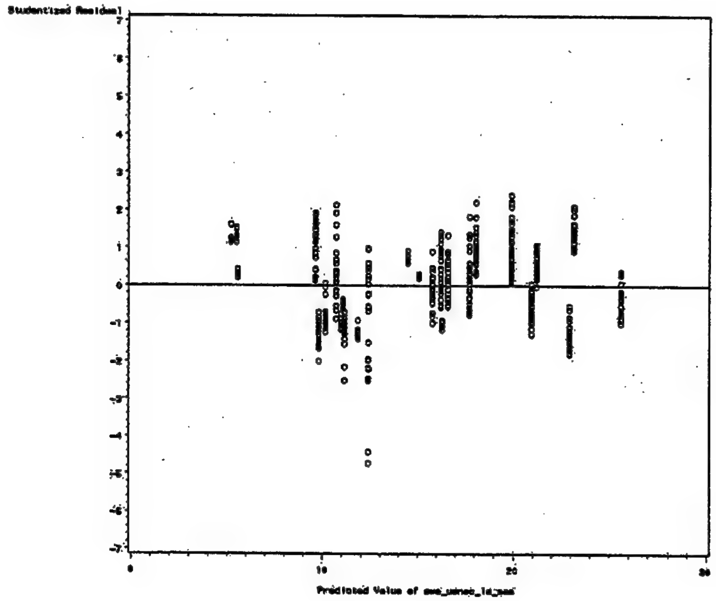

Figure 3.5. Residual plot with outliers.[5]

A general rule of thumb is that if the magnitude of t_i is significantly greater than r_i, then we have an outlier or high-influence-point. From Table 3.1, the observations are highlighted where the *R*-Student statistics are significantly different from the studentized residual. Since there is not a large discrepancy between r_i and t_i, we believe that none of the observations, even the points considered outliers, are influential. The HAT diagonal (h_{ii}) provides a measure of standardized difference from the observation to the data center in the regressors. The *R*-Student values and HAT diagonal values are proper diagnostics to isolate data points that are exerting disproportionate influence. A general guideline to detect high-leverage points is if $h_{ii} > 2p/n$. None of the observations for any of the MOO were considered high-leverage points because this was not an observational study but an experimental design.

Table 3.1. Points exhibiting high leverage.[5]

Variable Name	NEA				SWA			
	Observations	r_i	t_i	h_{ii}	Observations	r_i	t_i	h_{ii}
Red AC loss other	None	–	–	–	64	5.91	6.05	.034
USAF AC loss other	661	–4.20	–4.25	.035	185	6.86	7.10	.064
	666	6.11	6.27	.037	183	4.71	4.78	.055
	671	4.71	4.79	.034	187	4.81	4.89	.064
	425	4.01	4.06	.030	None	–	–	–
US N AC loss AA	507	–4.52	–4.58	.028	493	3.95	3.99	.042
	426	3.87	3.91	.032	None	–	–	–
Ally AC loss	None	–	–	–	60	4.00	4.04	.034
	None	–	–	–	299	4.91	4.99	.025
	None	–	–	–	315	5.77	5.90	.015
US Gnd ED loss	484	4.58	4.64	.017	612	5.40	5.51	.011
	305	6.11	6.27	.015	None	–	–	–
Ally Gnd ED loss	305	3.89	3.93	.018	None	–	–	–

When the studentized residual vs. predicted *y* plots were examined, there was no real trend or funnel effect in the scatter. From this, one can assume homogeneous variance. Studying the partial regression residual plots determines that none of the models are under-specified or in need of a transformation. From the plots, influential outliers are observed for USAF Air Craft loss due to other (see Figure 3.6). From Table 3.1, the most influential observations are for USAF Air Craft loss due to other; these points appear most clearly in the SWA plot on the right where the three significant outliers listed in Table 3.1 are seen the upper right portion of the residuals.

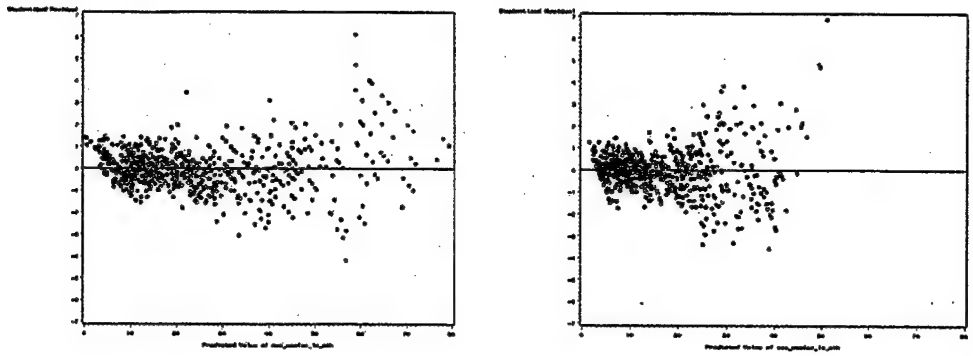

Figure 3.6. Residuals of USAF losses other than air combat and SAM.

3.2.4 Validation

Another 150 cases were modeled through JICM with different factor combinations than the 729 used to develop the models. The highlighted values in Table 3.2 indicate when the difference between the two adjusted R^2 measures exceeds 10%, when the average absolute difference (AAD) with respect to the average of the observed values exceeds 10%, or when the maximum absolute difference (MAD) with respect to observed value exceeds 20%.

Twenty-one of the 28 models predict very well. The seven exceptions are addressed in Table 3.3. There seems to be a problem with the three response variables dealing with the ground forces for both theaters. For the others, a transformation of the response variable or the use of weighted least squares may be useful, but not necessary, because they already have high adjusted R^2 values. Table 3.2 shows the response variables with validation problems and the associated reason.

Table 3.2. Summary of validation analysis.[5]

MOO	Adj R^2, %	Adj R^2 Validation, %	AAD/Avg Observed, %	MAD/Max Observed, %
NEA				
Halt Max %	80	71	5	13
Halt Time	61	45	12	29
Red AC Loss AA	95	93	3	7
Red AC Loss SAM	97	96	4	11
Red AC Loss Other	82	75	4	16
AFAC Loss AA	97	96	3	9
AFAC Loss SAM	98	96	4	15
AFAC Loss Other	94	84	16	25
NAC Loss AA	99	98	6	13
NAC Loss SAM	99	99	3	10
Allied AC Loss	99	97	3	10
Red Ground ED Loss	61	47	4	19
US Ground ED Loss	74	65	28	47
Allied Ground ED Loss	65	54	7	18
SWA				
Halt Max %	94	88	7	22
Halt Time	87	80	6	16
Red AC Loss AA	94	92	3	9
Red AC Loss SAM	94	85	7	15
Red AC Loss Other	91	91	3	13
AFAC Loss AA	89	89	5	15
AFAC Loss SAM	99	98	3	10
AFAC Loss Other	97	94	9	22
NAC Loss AA	98	98	5	11
NAC Loss SAM	99	98	3	23
Allied AC Loss	98	97	4	14
Red Ground ED Loss	68	33	14	25
US Ground ED Loss	66	64	37	52
Allied Ground ED Loss	52	21	6	15

Table 3.3. Summary of significant outliers.

Measure of Output	
NEA	
Halt Time	Due to the discrete nature of the outputs, there were large absolute differences between the predicted and the observed
AFAC Loss Other	Due to outliers (but still has very high adjusted R^2)
US Ground Loss	Due to outliers and the heterogeneous variance in the model
Allied Ground Loss	Just a very poorly fit model, something unexplained about the system
SWA	
Red Ground Loss	Due to outliers and the heterogeneous variance in the model
US Ground Loss	Due to outliers and the heterogeneous variance in the model
Allied Ground Loss	Just a very poorly fit model, something unexplained about the system

3.2.5 Third-Order Effects Explored

Given that there are two-way interactions, we examined three-way factors for their importance in explaining the MOO. A two-level resolution VII fractional factorial design was developed so that the three-way interactions were able to be estimated. The 1024 runs were sent to RAND to be run through JICM. With a two-level design, we can look only at linear effects, but we already knew about the curvature in the model through the previous three-level design. A complete three-level resolution VII design would have taken 20,000 runs. The interaction plots for the most significant three-way interaction for each measure of output were produced and evaluated.

Although it does appear that there are some significant three-way interactions, the second-order models already derived proved to be equally accurate and were used as the response surface prediction equations.

3.3 SUMMARY OF SURFACE DEVELOPMENT

Response surface methodology (RSM) was used in the attempt to accurately predict and optimize 14 MOO (responses) from the JICM. RSM consisted of designing a suitable experiment to evaluate 13 input variables that would allow the user to include significant first- and second-order effects in the model. Several model adequacy techniques were used to make sure the model would not be under- or over-specified. A specific second-order model was chosen from those techniques for each MOO. The polynomial approximations for every MOO are listed in Appendix B. Exploratory data analysis was used to check the validity of the least squares assumptions: normality and homogeneity of variances.

General conclusions and suggestions are as follows:

- USAF, NAVY, MR, PAT, and HELO are the most influential factors on the response variables, which are Halt Max %, Halt Time, Air Craft losses, and Ground losses.

- Three-way factors are significant and should be explored further.

- For future studies, perform a two-level screening experiment so that more factors can be looked at instead of a small, pre-chosen subset of factors. After the screening experiment has been performed and the number of input variables has been reduced, design one experiment that can estimate both the three-way interactions and curvature effects if it is desired to estimate the three-way interactions.

- The models produce better predictions in SWA than in NEA.

- The MOO for ground forces lost are predicted poorly in both theaters, but the majority of the other models predict very well. The poor prediction in some cases is a result of the coarse quantization of the MOO variables.

4 OPTIMIZATION

4.1 CONCEPT AND METHODOLOGY

4.1.1 Optimization Goals

The polynomial approximations discussed previously provide a representation of the simulation's "response" to a set of input values without having to develop and execute subsequent runs. This representation provides a rapid, low-cost predictive capability. By themselves, these equations provide the capability to answer questions such as, "For a given force mix, what is the expected outcome of a campaign?"

What the equations do not provide is an easy way to address questions of the type "What force mix is BEST used to achieve a DESIRED outcome?" It is easy to envision an iterative process of "guessing" a force mix, finding the predicted outcome, and then adjusting the force mix until an acceptable outcome is achieved. Such an approach has three major faults: (1) it is time consuming, (2) there is no assurance an acceptable solution can be found, and (3) even if a solution is found, there is no assurance that it is the best solution.

4.1.2 Optimization Formulation

Linear Formulation

The goal of the standard form of a linear optimization model is to find the values of input parameters that minimize (or maximize) an objective function:[11]

$$\text{Min (or Max)} \qquad \sum_{j=1}^{n} c_j x_j = Z$$

$$\text{s.t.} \qquad \sum_{j=1}^{n} a_{i,j} x_j = b_i, \qquad \forall i$$

$$x_j \geq 0, \qquad \forall j$$

where

x_j	is the jth decision variable (factor)
$a_{i,j}$	is a vector of coefficients for x_j
b_j	is a vector of constraining values
c_j	is a vector objective function coefficients

This a standard approach for optimizing systems of equations. If the response surface equations were linear, the above optimization formulation could be applied and the mathematics of linear optimization could be used. However, the response surface has

second-order elements which do not follow the format for linear optimization. Therefore, a non-linear formulation was used.

Nonlinear Formulation

The objective function for a nonlinear system relies on a more general formulation where each x_i is allowed to be a function, defined over all of X. For the specific problem this report is addressing, these equations are the polynomial approximation fit equations. The formulation now is, find the factor values that minimize (or maximize) the objective function, where[12]

$$\text{Min (or Max)} \qquad f(x_1, x_2, x_3, \ldots, x_n) = Z$$

$$\text{s.t.} \qquad g_1(x_1, x_2, x_3, \ldots, x_n) \quad (\leq, = or \geq)\ b_1$$

$$g_2(x_1, x_2, x_3, \ldots, x_n) \quad (\leq, = or \geq)\ b_2$$

M

$$g_m(x_1, x_2, x_3, \ldots, x_n) \quad (\leq, = or \geq)\ b_m$$

where

x_j	is the jth decision variable (factor)
f	is a one or more functions of x_j
g_m	is a set of functions constraining the objective function f
b_j	is a vector of constraining values

4.1.3 Optimization Model Description

In support of this proof of concept, specific questions the model might address are unknown and the basic design philosophy was to build as many options into the model as possible. The options are activated/deactivated by modifying input data values rather than modifying source code. This allowed the research team to quickly modify the optimization process and generate new results. Each component of the optimization implementation is discussed in detail.

Measures of Outcome

The MOO are the 28 polynomial approximations shown in Appendix B. They are divided into 14 equations for each theater. This allows the user to select which MOOs are important and allows for different levels of importance in the two scenarios.

Objective Function

Each MOO is assigned a weight (ω), which allows each MOO to have a variable "value," meaning that the overall contribution of that MOO is to be adjusted by the user. The objective function developed for this study is the sum of these weighted values:

$$Z = \sum(\omega_i MOO_i), \qquad \forall MOO.$$

The objective function is used to drive the search of the response surface; however, the actual value of the objective function has very little real-world meaning. The user input weights can range in value from –1 to +1. A weight of zero eliminates the MOO from consideration, a positive weight leads to maximization, and a negative weight leads to minimization. The magnitude of the weight is an indication of relative importance of that MOO compared to others. In a typical optimization problem, the MOO of interest would be weighted and all others would be assigned a weight of zero. An assigned weight of zero indicates that the MOO is free to take any value that best supports the minimization (or maximization) of the MOO of interest.

Weighting combinations of MOOs can lead to unexpected results. For example, one could attempt to minimize the losses of Blue forces. The model recommends that to minimize Blue losses, the commander should minimize the number of forces employed. While this leads to minimal losses, it also leads to losing the conflict.

Another complication with multiple MOOs being active in the objective function is that the values of the MOOs are not scaled with respect to each other. This allows some MOOs to dominate others. For example, the loss of a few aircraft (which is counted at the individual level) can outweigh the measure of outcome "percent of the time Red achieves its object" (which is scaled to 0–1). Great care was taken to ensure that this issue did not negatively affect the research.

Constraints

The model incorporates upper and lower bounds on each of the MOOs. While this constraint is not strictly required (it could be enforced by bounding decision factor values), incorporating it constrains the decision space to a region consistent with the initial data generated from JICM. One basic constraint on all the decision factors is that the model bounds each to the extreme values used in the JICM runs. These constraints are included in the model to restrict the optimization to the response surface region generated by the JICM data. Since the model reads MOOs bounds from input tables, a user of the optimization can easily modify those boundaries. By further constraining the MOO boundaries, the user can set up a problem that would maximize a MOO (e.g., Red aircraft losses) subject to an additional constraint of not allowing the conflict to exceed some number of days (e.g., Halt time < 8 days).

There are 13 decision factors for each of the scenarios, which are the independent variables in the MOO equations and the domain of the response surface. Each of the decision factors has been scaled to [–1,+1] before the response surface curves were generated. This scaling is maintained within the optimization model and its data tables. Therefore, the results of the optimization must be "un-scaled" to provide easy-to-interpret results. Some of these are true decision factors over which the Blue commander has some direct control (e.g., the initial Blue force mix); others are factors that are implemented as pseudo-decisions for modeling simplicity.

The model includes a constraint that the total forces committed to all scenarios (if running simultaneously) cannot exceed the total amount available. The Blue force may also be constrained by other factors unique to the environment(s) (e.g., the number of ground-based aircraft cannot exceed the airfield capacity), force configuration and

doctrine constraints (e.g., helicopter forces would not be deployed with supporting ground forces), and physical constraints (e.g., the number of munitions used cannot exceed the firing capacity of the number of firing platforms). Determining the values of such constraints is beyond the scope of this project, but the optimization model includes input tables to allow them to be incorporated. The model also includes splitting the decision factors into subcategories of platforms and munitions to allow for incorporation of munitions-platform constraints, but these have not been added to the model.

Some of the 13 decision factors included in the model are beyond the control of the Blue commander (e.g., the Red force mix). There may be cases when the Blue commander can indirectly influence some of them (e.g., a preemptive strike against weapons of mass destruction delivery platforms or opening another front).

4.1.4 Optimization Model

The optimization model is a nonlinear, multiple attribute deterministic optimization. The implementation is relatively simple. The model maximizes the object function Z, subject to a set of linear and nonlinear constraints.

Max $\quad Z = \sum(\omega_{i,s} * \mathrm{MOO}_{i,s})$, over all MOOs and scenarios

s.t. $\quad$ Lower Bound $\mathrm{MOO}_{i,s} \leq \mathrm{MOO}_{i,s} \leq$ Upper Bound $\mathrm{MOO}_{i,s}$

Lower Bound $\mathrm{DF}_{i,s} \leq \mathrm{DF}_{i,s} \leq$ Upper Bound $\mathrm{DF}_{i,s}$

$\sum(\mathrm{DF}_{i,s}) \leq$ Global Upper Bound DF_i, summed over all scenarios

4.2 EXPLORING OPERATIONAL SITUATIONS

Two operational situations (OPSITs) were developed to demonstrate the function of this methodology.

4.2.1 OPSIT 1 (SWA Base Case)

This OPSIT occurs in SWA and consists of Red forces invading Saudi Arabia. The Joint Forces Commander's intent is to halt the offensive as quickly as possible to limit the terrain gained by Red. Based on available intelligence estimates, the RED side is expected to commit the majority of their forces to the campaign but retain forces for internal security. In addition, the RED commander's intent is to move as quickly as possible to secure terrain before international pressures can be brought to bear. The RED commander also hopes that early success will demoralize the Blue forces while encouraging other countries to support the offensive.

Constraints are based on the intelligence estimate that the RED forces' factors (RSAM and SCUD) are set to 75% of maximum. Based on the Red commander's intent of rapid movement, the Red movement rate is set to maximum. The objective function models the Blue commander's objective of ending the operations quickly, the "Halt_Time" weight is set to −1 for the SWA scenario. All other weights are set to zero, eliminating them from consideration.

The model returned a halt time of 4.5 days, which is the minimum number of days required to halt the Red advance. This is the bound of the response surface, which is what one would expect of a single MOO in the objective function. Table 4.1 gives the scaled force structure that corresponds to this halt time. Note that decision factors ARTY, PAT, TLAM, SCUD, and RSAM are not included in the MOO for "Halt_Time" in SWA (see Appendix B), so they are uncontrolled for this problem and their values make no contribution to the objective function.

Table 4.1. Optimum decision factors values for OPSIT 1.

HELO	1.00
ARM	–1.00
ATCM	1.00
USAF	0.97
ARTY	0.0
NAVY	1.00
INF	1.00
MR	1.00
PAT	–0.49
TLAM	0.57
SCUD	0.75
RSAM	0.75
JSOW	–1.00

Table 4.2 contains the values of all the MOOs for this OPSIT. While the model predicts that the advance was halted in 4.5 days, the Red forces were able to penetrate 67% of the way to their objective. The coalition forces lost close to 100 aircraft (75 of them U.S.) and a significant portion (85%) of a division (almost exclusively GCC). Considering that the United States entered the conflict with less than 400 aircraft and sustained a lose of almost 20% of them and the GCC entered the conflict with 8 bridges and lost almost 50% of them, it is reasonable to assume that the Blue commander would not consider that halting the invasion in 4.5 days was a successful campaign.

Table 4.2. MOO values for OPSIT 1, base case.

Halt_Max_Per_Cent	0.67
Halt_Time	4.50
Red_AC_loss_due_to_AA	32.17
Red_AC_loss_due_to_SAM	32.07
Red_AC_loss_due_to_other	126.31
USAF_AC_loss_due_to_AA	7.64
USAF_AC_loss_due_to_SAM	18.21
USAF_AC_loss_due_to_other	26.07
US_NAC_loss_due_to_AA	1.21
US_NAC_loss_due_to_SAM	21.35
Ally_AC_loss	17.92

Red_Ground_ED_loss	3.45
US_Ground_ED_loss	0.01
Ally_Ground_ED_loss	0.85

4.2.2 OPSIT 1, Excursion 1a (Set Red Penetration)

Based on results from the base case of OPSIT 1, the commander directs an excursion to examine limiting the depth of the Red advance to 50% of that achieved in the base case.

The model setup remains the same as in the base case, except for setting a constraint on the depth of Red's penetration. This is done by setting the upper bound of "Halt_Max_Per_Cent" for the SWA scenario to 0.33 (50% of the previous 0.67).

The model determined that this set-up is *infeasible*. When the Red force elects a movement rate of 1.0, there is no Blue option that can prevent the Red forces from achieving at least a 33% penetration toward their objective.

4.2.3 OPSIT 1, Excursion 1b (Limit Red Penetration)

The Blue commanders might ask questions such as, "What is the minimum Red penetration I can expect?" The next set of options explored was to use the model to determine the minimum penetration if the conflict were allowed to continue beyond the 4.5 days. For this excursion, the objective was to minimize the penetration, subject to the conflict not exceeding 11 days (the upper boundary for the response curves). The weight for the "Halt_Max_Per_Cent" for the SWA is set to –1 to minimize that value, the weight of "Halt_time" is set to zero to remove it from the objective function, the upper boundary of Halt_Max_Per_Cent is returned to 1, the upper boundary for the Halt_Time for the SWA is set to 11 days, and the rest of the model setup is left unchanged.

The Halt_Max_Per_Cent reported for this setup was 0.59, indicating that the Red force achieved a 59% penetration toward their objective, which occurred at 4.87 days into the conflict. The decision variable values that produced these results are given in Table 4.3. As previously observed, TLAM and RSAM are not factors in the equation to calculate "Halt_Max_Per_Cent," so they are not under control of the model (for this specific run) and their values have no meaning.

Table 4.3. Optimum decision factors values for OPSIT 1, Excursion 1b.

HELO	1.00
ARM	1.00
ATCM	1.00
USAF	1.00
ARTY	1.00
NAVY	1.00
INF	1.00
MR	1.00
PAT	1.00

TLAM	–1.00
SCUD	0.75
RSAM	0.75
JSOW	1.00

Table 4.4 contains the values of the MOOs for this model run. It indicates that the Blue forces loose 13.6 fewer aircraft, while Red aircraft losses rise by 27.7 aircraft. The Blue ground force losses are unchanged, while the Red ground forces losses dropped slightly (0.03 ED). By allowing the conflict to last an additional 9 hours (4.5 versus 4.87 days) and changing the Blue tactics, the Blue commander would be able to simultaneously

- Reduce the depth of Red penetration (67% versus 59%)
- Reduce Blue aircraft losses (92.4 versus 87.8), and
- Increase the attrition of Red aircraft (190.6 versus 218.2).

Table 4.4. MOO values for OPSIT 1, Excursion 1b.

Halt_Max_Per_Cent	0.59
Halt_Time	4.87
Red_AC_loss_due_to_AA	36.74
Red_AC_loss_due_to_SAM	52.94
Red_AC_loss_due_to_other	128.54
USAF_AC_loss_due_to_AA	8.34
USAF_AC_loss_due_to_SAM	18.45
USAF_AC_loss_due_to_other	11.43
US_NAC_loss_due_to_AA	1.37
US_NAC_loss_due_to_SAM	21.30
Ally_AC_loss	17.93
Red_Ground_ED_loss	3.42
US_Ground_ED_loss	0.01
Ally_Ground_ED_loss	0.85

4.2.4 OPSIT 1, Excursion 2 (Limit Blue Loses)

The Blue commander's review of the base case results also reveals the unacceptable level of Blue losses. This was examined to find alternatives to reduce those losses. The Red options were reset to the base case settings. All the user weights were set to zero except for those related to Blue forces losses, which were all set to negative values to create an objective function to minimize Blue losses (Table 4.5). Optimum decision factor values are shown in Table 4.6.

Table 4.5. Non-zero weight for OPSIT 1, Excursion 2a.

USAF_AC_loss_due_to_AA	–1
USAF_AC_loss_due_to_SAM	–1
USAF_AC_loss_due_to_other	–1
US_NAC_loss_due_to_AA	–1
US_NAC_loss_due_to_SAM	–1
Ally_AC_loss	–1
US_Ground_ED_loss	–1
Ally_Ground_ED_loss	–1

Table 4.6. Optimum decision factors values for OPSIT 1, Excursion 2a.

HELO	–0.22
ARM	–0.31
ATCM	1.00
USAF	–1.00
ARTY	–0.06
NAVY	1.00
INF	0.34
MR	1.00
PAT	1.00
TLAM	0.63
SCUD	0.75
RSAM	0.75
JSOW	1.00

Compared to the base case, this excursion reduces the USAF and helicopter forces committed to the conflict while slightly increasing the amount of Armor and leaving the ATCM and Navy components unchanged (Table 4-7).

Table 4.7. Blue force structure for OPSIT 1, base case vs. Excursion 2a.

	Base Case	Excursion 2a
HELO	1.00	–0.22
ARM	–1.00	–0.31
ATCM	1.00	1.00
USAF	0.97	–1.00
ARTY	0.0	–0.06
NAVY	1.00	1.00
INF	1.00	0.34
MR	1.00	1.00
PAT	–0.49	1.00
TLAM	0.57	0.63
SCUD	0.75	0.75

RSAM	0.75	0.75
JSOW	−1.00	1.00

Compared to the base case, under the conditions of Excursion 2a this alternative

- Extended the conflict almost a day (4.5 versus 5.39 days),
- Increased the depth of Red's penetration (67% versus 90%),
- Reduced Blue aircraft losses (92.4 versus 71.6),
- Increased Blue ground losses (0.86 versus 0.88 EDs),
- Reduced Red aircraft losses (190.6 versus 178.2), and
- Reduced Red ground losses (3.45 versus 2.65 EDs).

MOO values are given in Table 4.8.

Table 4.8. MOO values for OPSIT 1, Excursion 2a.

Halt_Max_Per_Cent	0.90
Halt_Time	5.39
Red_AC_loss_due_to_AA	33.77
Red_AC_loss_due_to_SAM	58.85
Red_AC_loss_due_to_other	85.54
USAF_AC_loss_due_to_AA	5.63
USAF_AC_loss_due_to_SAM	9.60
USAF_AC_loss_due_to_other	7.87
US_NAC_loss_due_to_AA	1.41
US_NAC_loss_due_to_SAM	25.04
Ally_AC_loss	22.03
Red_Ground_ED_loss	2.65
US_Ground_ED_loss	0.04
Ally_Ground_ED_loss	0.84

4.2.5 OPSIT 1, Excursion 2b (Force Scaling)

As mentioned, in the way the model is applied thus far there is a scaling problem when multiple MOOs are included in an objective function. Excursion 2b illustrates that issue. The model equates the loss of a single aircraft with the loss of a single ground division. Since a notional division consists of 20,000 soldiers and a notional aircraft consists of a crew of 2, equating the two values leads to distorted results. In excursion 2b, the loss of 0.02 additional EDs is offset by saving 21 aircraft. This implies that the 400 additional ground causalities (20000 • 0.02) are equal to the prevention of 42 (20.8 • 2) air losses.

Equating the number of causalities (one could select a different metric) produces the scale factor that one ED equals 10,000 aircraft. This can be input to the model by modifying the weights used in the objective function (Table 4.9).

Table 4.9. Non-zero weight for OPSIT 1, Excursion 2b.

USAF_AC_loss_due_to_AA	−0.0001
USAF_AC_loss_due_to_SAM	−0.0001
USAF_AC_loss_due_to_other	−0.0001
US_NAC_loss_due_to_AA	−0.0001
US_NAC_loss_due_to_SAM	−0.0001
Ally_AC_loss	−0.0001
US_Ground_ED_loss	−1
Ally_Ground_ED_loss	−1

Adjusting the weights to correct for the scaling factor issues caused the model to return large components of HELO, ARM, UASF, and TLAM to the Blue force mixture. As before, ARTY, INF, and JSOW are not included in the MOO equations (Table 4.10). MOO values are given in Table 4.11.

Table 4.10. Optimum decision factors values for OPSIT 1, Excursions 2a and 2b.

	2a	2b
HELO	−0.22	0.81
ARM	−0.31	1.00
ATCM	1.00	1.00
USAF	−1.00	1.00
ARTY	−0.06	1.00
NAVY	1.00	1.00
INF	0.34	0.93
MR	1.00	1.00
PAT	1.00	1.00
TLAM	0.63	1.00
SCUD	0.75	0.75
RSAM	0.75	0.75
JSOW	1.00	0.0

Table 4.11. MOO values for OPSIT 1, base case and Excursions 2a and 2b.

	OPSIT 1, Base Case	Excursion 2a	Excursion 2b
Halt_Max_Per_Cent	0.67	0.90	0.64
Halt_Time	4.50	5.39	4.91
Red_AC_loss_due_to_AA	32.17	33.77	28.92
Red_AC_loss_due_to_SAM	32.07	58.85	44.93

Red_AC_loss_due_to_other	126.31	85.54	123.07
USAF_AC_loss_due_to_AA	7.64	5.63	6.61
USAF_AC_loss_due_to_SAM	18.21	9.60	18.54
USAF_AC_loss_due_to_other	26.07	7.87	11.24
US_NAC_loss_due_to_AA	1.21	1.41	1.03
US_NAC_loss_due_to_SAM	21.35	25.04	21.3
Ally_AC_loss	17.92	22.03	17.5
Red_Ground_ED_loss	3.45	2.65	3.33
US_Ground_ED_loss	0.01	0.04	0.009
Ally_Ground_ED_loss	0.85	0.84	0.83
Total Blue casualties	17,357	17,743	16,932

4.2.6 OPSIT 1, Excursion 3 (Simultaneous Theaters)

In addition to the SWA conflict, the political situation in NEA deteriorates to the point that the probability of a Red invasion in that second theater is high. The Blue forces commander must allocate sufficient forces to both theaters but is constrained by the total available force structure.

The NEA intelligence estimate is that, as in SWA, the Red commander's intent is to move as quickly as possible to secure his objectives before other countries become involved. However, the NEA commander is not concerned with either a second front or withholding a large reserve for internal population control.

Constraints are based on the intelligence estimate; Red forces' factors RSAM and SCUD are set to 90% of maximum. Based on the Red commander's intent of rapid movement, the Red movement rate is set to maximum. Since each of the Red forces is operating independently, they are each allowed to commit all of their force to their individual theater.

The Blue forces commander is allowed to move forces between theaters, but the sum of forces committed to both theaters cannot exceed the total Blue force structure. The model is allowed to reallocate only 1/3 of each type of force between the theaters; thus, each theater must have a minimum force mix equal to 1/3 of the total force. To achieve this, the maximum value for the sum of the total forces assigned is set to –1.

The Blue commander's objective (and objective function) is to win both conflicts, which equates to halting both invasions short of their objectives. The first question to be addressed is, "Is there a Blue force mixture that can achieve this combined objective?" To model this, the weight of Halt_Max_Per_Cent (the variable for depth of Red penetration) is set to –1 for both theaters. The negative weight is to minimize the penetration, and the magnitude of the weights is the same since failure in either theater would be considered a mission failure.

Table 4.12 contains the force assignments for the two theaters. Recall that a 0 value in this table reflects sending 2/3 of the total force to that theater. MOO values are given in Table 4.13.

Table 4.12. Optimum decision factors values for OPSIT 1, Excursions 3a.

	NEA	SWA
HELO	–1.00	0.0
ARM	0.0	–1.00
ATCM	0.0	–1.00
USAF	0.0	–1.00
ARTY	0.0	–1.00
NAVY	0.0	–1.00
INF	0.0	–1.00
MR	1.00	1.00
PAT	–1.00	0.0
TLAM	–0.29	–0.71
SCUD	0.90	0.75
RSAM	0.90	0.75
JSOW	–0.80	–1.00

Table 4.13. MOO values for OPSIT 1, Excursion 3a.

	NEA	SWA
Halt_Max_Per_Cent	0.99	0.98
Halt_Time	8.57	5.99
Red_AC_loss_due_to_AA	128.39	33.69
Red_AC_loss_due_to_SAM	46.11	54.2
Red_AC_loss_due_to_other	288.94	93.88
USAF_AC_loss_due_to_AA	4.81	5.52
USAF_AC_loss_due_to_SAM	5.6	14.57
USAF_AC_loss_due_to_other	51.21	18.63
US_NAC_loss_due_to_AA	5.96	0.40
US_NAC_loss_due_to_SAM	10.40	13.58
Ally_AC_loss	29.22	34.52
Red_Ground_ED_loss	2.29	2.25
US_Ground_ED_loss	0.18	0.06
Ally_Ground_ED_loss	1.55	0.83

The model indicates that the Red forces penetrated 99% of the way to their NEA objective and 98% of the way to their SWA objective in 8.57 and 5.99 days, respectively. Within the resolution of this model, one would have to conclude that both Red invasions were successful. While Red losses were significant—651 out of 1105 aircraft (almost 60%) and just over 2.5 divisions—Blue losses were devastating. Of the 229 UASF aircraft, 100 were destroyed; of the 837 allied aircraft, 64 were destroyed; of the 2 divisions and 8 separate brigades, 2.6 equivalent divisions were lost.

Since this is the best outcome that can be expected and it used all the available U.S. forces, the Blue commander will have to do something outside of the model to achieve victory.

5 CONCLUSIONS

5.1 CONCLUSION

This report summarizes research, evaluates product quality, and assesses the viability of an RSM approach. This assessment takes into consideration the interests of JHU/APL as well as emerging technology. Overall it is an effort to develop a statistical tool or analytical methodology appealing to military sponsors developing future combat technologies.

The results of this effort support the thesis that simulation modeling and an optimization process can be used in concert to examine military systems, capabilities, and warfare areas to provide analytical insight into the trade-offs existing between contributing systems/capabilities and warfare areas. We are able to evaluate questions of interest to military sponsors and provide fast, analytic course of action analysis considering every aspect of a campaign. The sponsor can request excursions, and these can be produced and evaluated on-the-spot.

5.2 LESSONS LEARNED

This type of analysis is not cheap; it demands commitment of manpower and money and an intellectual investment from experienced analysts to ensure small details are not overlooked.

5.2.1 Simulation Modeling

The primary purpose of most simulation studies is the approximation of system parameters with the objective of identifying values that optimize specific system performance measures. A simulation study consists of several steps, such as experimental design, data collection, verification, validation, and data analysis. There are two types of simulations: Terminating Simulations and Steady-State Simulations. In general, the methods of analyzing each are different.[13] Stopping conditions for the JICM produced both types for this research. The stopping conditions of the simulation must be resolved to ensure a quality comparison. In this research, a battle that ends after 1 day is compared to a battle that was terminated at 15 days without a winner. Examining entire campaigns magnifies this problem. Simulation, as compared to closed-form models, is the appropriate approach to data generation for a study of this type. It provides large and diverse data sets but requires the investment of set-up time to establish the starting parameters.

5.2.2 Response Surface Methodology

Developing response surface approximation equations that allow the analyst to exhaustively map the measures of outcome was beneficial in this study because it provided a high-fidelity perspective of the expected response. However, RSM is cumbersome and has limited scope. The approximations are based only on the starting assumptions. If any of the input parameters change in performance, structure, or quantity (outside of the established bounds), the experimental design is in jeopardy.

5.2.3 Trade Space Analysis

This is the right way to look at the problem but it is driven by fidelity. Our knowledge of the trade space comes from defining nodes within the space; the closer the nodes, the better our knowledge of how to move between (or trade) their values. A sparse trade space representation has a high error in extrapolation between the nodes. A dense trade space has low error but intense computational requirements.

5.2.4 Data Production

JICM is too aggregate a model for analysis of specific warfighting systems. Models used in the future must be able to represent individual combat platforms (a collection of systems) but operate with a strategic or global view.

An appropriate scaling for comparison of MOO must be developed and agreed upon. An arbitrary scaling method was presented in this report but a military sponsor may opt for a much different base comparison of asset value.

5.2.5 Optimization

The algorithms and GAMS code used for this research provided useful results that are applicable within the limited scope of the campaigns analyzed. Conceptually the optimization process works, but the application needs further research to develop a broadly applicable methodology. The method employed here was labor intensive.

5.3 THE NEXT STEP

5.3.1 Broader Application

This methodology is viable for examining warfare capabilities. The logical extension of this process is its application in a much broader study. Future application must consider diverse input parameters and more MOO. For example, larger operational theaters with more complicated movement networks, the effects on strategic lift capabilities, naval deep water engagements, and multiple simultaneous theaters of war can be examined.

5.3.2 Model Construct

Response surface methodology is used here to generate a mathematical representation of each MOO. This process helped both in the understanding and explanation of platform/system interaction. RSM is a cumbersome task and, although it yields a vision of the entire solution space, it is not necessary to understand the entire response mapping for all MOEs. Future research could take advantage of other techniques.

The most productive future course of action seems to be integrated optimization. Future work using this approach should combine simulated model results with an optimization process in a feedback loop so that a single simulation run feeds the optimization and the optimization dictates input values for successive runs. Here the optimization process trades interim results with the data-producing software to make logical, improving changes to parameter values for each iteration. In this way, various starting points may be examined in the solution space with each progressing toward an

optimal allocation of assets based on the optimization. Thus, instead of mapping the entire response surface for each MOE and then evaluating the union of all surfaces to find a feasible region, a direct path is constructed to an optimal solution. A starting point must be established using this methodology and care must be taken to avoid local maxima/minima that are suboptimal. It is recommended that multiple starting points be used within the region of interest and that an aggressive perturbation process be developed to move beyond suboptimal points.

5.3.3 Soft Factors

Logistics, communications, morale, and command are very hard to model, and many developers are trying to incorporate these types of factors into their models. These can be analyzed using the same methodology presented in this report once adequate models for these factors are available.

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Appendix A

PARTIAL JICM OUTPUT DATA FILES

Southwest Asia

		N	Halt	Halt Days	Halt > 15 days	Red AC Start	RED AC loss - AA	RED AC loss - SAM	RED AC loss - other	USAF AC - start	USAF AC loss - AA	USAF AC loss - SAM	USAF AC loss - other	USN AC - start	USN AC loss - AA	USN AC loss - SAM	USN AC loss - other	ALLY AC - start	ALLY AC loss	RED Ground ED - start	RED Ground ED - loss	US Ground ED - start	US Ground ED - loss	ALLY Ground ED - start	ALLY Ground ED - loss
All 'L'	x 0 0 0 0	1	0.959	10.5	0	325	38.019	35.491	138.446	103	6.621	7.364	17.445	54	0.517	6.061	0	484	21.792	5.02	2.589	0.391	0.103	1.574	0.884
	x 0 0 0 1	2	0.301	4.5	0	325	35.117	23.485	141.142	217	7.576	18.061	13.742	162	1.332	20.528	0	484	18.61	5.02	3.823	0.438	0.01	1.574	0.66
	x 0 0 0 2	3	0.598	7	0	325	35.942	28.02	123.256	168	9.964	16.191	13.072	108	0.662	16.897	0	484	23.4	5.02	2.573	0.481	0.013	1.574	0.874
	x 0 0 0 3	4	0.3	4.5	0	325	31.415	23.752	118.774	217	7.676	14.107	9.837	108	0.838	10.442	0	484	15.869	5.02	2.542	0.431	0.01	1.574	0.659
	x 0 0 0 4	5	0.595	7	0	325	32.234	28.515	120.272	168	10.012	22.488	13.027	54	0.32	11.015	0	484	32.284	5.02	2.528	0.476	0.011	1.574	0.876
	x 0 0 0 5	6	0.898	10	0	325	50.968	35.325	129.728	103	8.659	9.175	15.782	162	2.242	23.929	0	484	23.008	5.02	2.499	0.521	0.091	1.574	0.882
	x 0 7 2 6	727	0.723	5	0	325	27.994	49.003	105.633	168	7.38	10.777	9.261	108	0.79	10.761	0	484	15.942	5.02	2.53	1.084	0.007	1.574	0.868
	x 0 7 2 7	728	0.8	7	0	325	29.613	69.118	86.517	103	6.292	14.586	10.909	54	0.373	12.397	0	484	33.779	5.02	2.588	1.129	0.084	1.574	0.757
	x 0 7 2 8	729	0.816	7	0	325	37.202	57.339	136.108	217	8.669	17.696	13.494	162	1.45	20.023	0	484	17.804	5.02	2.5	1.174	0.06	1.574	0.739
mean			0.74503155	6.46844993	0	325	33.5862291	42.8844801	117.39958	162	7.48715638	14.6769806	16.3098587	108	0.91600412	14.7390206	0	484	22.4366831	5.02	2.58768999	0.78255556	0.03878484	1.574	0.82115364
std dev			0.18959395	1.40801978	0	0	5.81267431	11.5355994	18.7654505	46.6581854	1.36941818	5.29724664	10.6556284	44.1210871	0.50800315	5.54389228	0	0	5.80663629	3.9359E-07	0.39518507	0.25520179	0.02875305	2.1717E-07	0.07398406
min			0.299	4.5	0	325	23.124	22.031	75.215	103	4.828	6.332	3.078	54	0.231	5.663	0	484	13.747	5.02	1.222	0.391	0.002	1.574	0.657
max			1	11	0	325	53.743	70.88	170.645	217	11.259	28.143	63.883	162	2.418	25.753	0	484	40.685	5.02	3.985	1.174	0.174	1.574	0.887

Figure A.1. Representative SWA numbers with summary statistics.

Northeast Asia

		N	Halt	Halt Days	Halt > 15. days	Red AC Start	RED AC loss - AA	RED AC loss - SAM	RED AC loss - other	USAF AC - start	USAF AC loss - AA	USAF AC loss - SAM	USAF AC loss - other	USN AC - start	USN AC loss - AA	USN AC loss - SAM	USN AC loss - other	ALLY AC - start	ALLY AC loss	RED Ground ED - start	RED Ground ED - loss	US Ground ED - start	US Ground ED - loss	ALLY Ground ED - start	ALLY Ground ED - loss
All 'L'	x 0 0 0 0	1	0.663	12.5	0	780	149.484	59.594	290.878	103	3.651	3.367	20.012	54	3.389	3.824	0	353	27.354	5.163	2.679	0.391	0.111	1.863	1.733
	x 0 0 0 1	2	0.751	11.5	0	780	121.895	52.174	304.849	217	5.328	6.045	22.682	162	7.451	12.694	0	353	23.441	5.163	2.763	0.438	0.038	1.863	1.33
	x 0 0 0 2	3	0.751	11	0	780	121.398	51.013	320.727	168	4.975	5.189	19.913	108	5.598	9.638	0	353	28.032	5.163	2.903	0.481	0.051	1.863	1.369
	x 0 0 0 3	4	0.751	11.5	0	780	122.11	58.283	304.535	217	5.793	5.807	22.685	108	5.483	7.228	0	353	20.928	5.163	2.742	0.431	0.027	1.863	1.333
	x 0 0 0 4	5	0.751	10.5	0	780	110.051	51.205	335.708	168	5.068	6.593	19.885	54	2.377	5.521	0	353	35.572	5.163	2.637	0.476	0.044	1.863	1.399
	x 0 0 0 5	6	0.751	999	1	780	172.241	55.681	303.478	103	3.272	3.003	22.991	162	11.173	13.632	0	353	29.08	5.163	2.183	0.521	0.06	1.863	1.349
	x 0 7 2 6	727	0.77	11.5	0	780	98.674	108.121	285.18	168	4.779	4.354	18.069	108	4.132	7.344	0	353	19.25	5.163	2.641	1.084	0.087	1.863	1.121
	x 0 7 2 7	728	1	8.5	0	780	102.383	108.084	288.602	103	3.207	4.196	11.739	54	2.049	6.261	0	353	30.562	5.163	2.488	1.129	0.211	1.863	1.389
	x 0 7 2 8	729	0.805	999	1	780	133.829	93.436	352.627	217	5.765	5.947	23.525	162	8.402	12.442	0	353	24.084	5.163	2.193	1.174	0.092	1.863	1.124
mean			0.8283788	149.153635	0.16460905	780	121.270671	79.218823	297.92584	162	4.60281481	5.02080247	24.3473004	108	5.4173251	8.74314952	0	353	26.8425556	5.163	2.5823059	0.78255556	0.06840192	1.863	1.35435254
std dev			0.09909777	343.014605	0.37108194	0	18.2918556	22.0184882	35.8782789	46.6581854	0.96432019	1.62513521	16.8815037	44.1210871	2.63357369	3.25429508	0	0	5.74725347	0	0.23046858	0.25520179	0.05617143	0	0.16832967
min			0.698	6	0	780	84.503	38.135	203.597	103	2.519	2.535	3.066	54	1.719	3.525	0	353	16.312	5.163	1.882	0.391	0.021	1.863	0.952
max			1	999	1	780	174.753	126.409	375.618	217	6.415	9.248	83.609	162	11.399	14.557	0	353	44.118	5.163	3.128	1.174	0.291	1.863	1.863

Figure A.2. Representative NEA numbers with summary statistics.

Appendix B
POLYNOMIAL APPROXIMATIONS

NEA	***Model (With coded variables)***
NEA Halt Max % Adj R^2 = 79.89%	.8197+.0768MR-.0531HELO-.0269ARM-.0162ATCM-.0134USAF-.0123ARTY-.0113NAVY-.0110INF-.0064PAT-.0351MR*HELO-.0208MR*ARM-.0103MR*USAF-.0125MR*ATCM-.0082MR*ARTY-.0102MR*INF-.0080MR*NAVY+.0130ARM^2
NEA Halt Time Adj R^2 = 60.51%	12.571-1.293MR+.774ARM+.594USAF+.553ATCM+.361PAT-.311HELO+.041NAVY+.3076INF+1.401MR*HELO-.614ARM*HELO .617MR*ARM+.523MR*ATCM+.330MR*NAVY-.279ARTY*HELO+.307MR*INF-.745HELO^2-.507MR^2-.393ARM^2
NEA Red AC loss due to AA Adj R^2 = 94.84%	112.69-12.58TLAM-11.01PAT+9.96NAVY-7.48USAF+1.53RSAM-.76MR+2.41TLAM*USAF-1.84PAT*TLAM+1.33SCUD*USAF-1.22TLAM*RSAM–1.20SCUD*PAT–1.06TLAM*NAVY+.99MR*HELO+5.97TLAM^2+6.90USAF^2
NEA Red AC loss due to SAM Adj R^2 = 96.54%	79.85+25.53PAT+4.02TLAM-2.50USAF-2.30NAVY-2.08MR+.79ARM+.80ATCM+.10HELO-.43SCUD+1.96MR*HELO+1.75PAT*TLAM-1.78PAT*USAF-1.33PAT*NAVY+.86SCUD*USAF+3.46USAF^2-2.89PAT^2-1.50TLAM^2
NEA Red AC loss due to other Adj R^2 = 81.70%	322.59+29.53USAF-14.80TLAM-10.93MR+6.40ARM+4.60ATCM-3.27SCUD+2.83INF-3.46NAVY+10.98MR*HELO+5.72MR*ARM -4.27ARM*HELO-4.90TLAM*USAF+4.82MR*ATCM+2.95MR*NAVY-13.89USAF^2-10.92TLAM^2 –7.16HELO^2-5.03MR^2
NEA USAF AC loss due to AA Adj R^2 = 96.54%	4.87+1.12USAF-.103SCUD-.045TLAM-.039MR+.021RSAM-.010PAT-.004HELO-.180PAT*USAF+.177SCUD*USAF-.132TLAM*USAF-.059PAT*TLAM+.044MR*HELO+.041USAF*RSAM-.028USAF*NAVY-.437USAF^2+.042TLAM^2
NEA USAF AC loss due to SAM Adj R^2 = 98.13%	5.22+1.66USAF-.775NAVY .607RSAM-.102JSOW+.067PAT-.057SCUD+.268USAF*RSAM-.211NAVY*RSAM-.102JSOW*RSAM-.079JSOW*USAF+.050JSOW*NAVY-.327RSAM^2-.081USAF^2+.013NAVY^2+.102JSOW^2
NEA USAF AC loss due to other Adj R^2 = 93.97%	24.32-13.64PAT+11.68SCUD+3.90USAF-2.52MR+1.68ARM .84ATCM -.41HELO+.62INF-6.45SCUD*PAT+2.74PAT*USAF+2.29SCUD*USAF+1.68MR*PAT-1.40ARM*HELO+1.32MR*ARM-.95MR*SCUD-1.11PAT*ARM .95SCUD*ARM+1.00MR*ATCM+.75MR*NAVY+.74ARM*USAF+2.93PAT^2-1.35HELO^2-1.54USAF^2
NEA US NAC loss due to AA Adj R^2 = 99.12%	5.10+2.99NAVY-.71TLAM-.62PAT-.37USAF+.04RSAM-.039MR-.398TLAM*NAVY-.326PAT*NAVY-.199USAF*NAVY-.095PAT*TLAM+.072PAT*USAF-.073SCUD*PAT+.259USAF^2-.156NAVY^2
NEA US NAC loss due to SAM Adj R^2 = 99.47%	9.86+3.62NAVY+1.39RSAM-.48USAF+.324NAVY*RSAM-.249USAF*RSAM-.120USAF*NAVY -.874RSAM^2-.794NAVY^2
NEA Ally AC loss Adj R^2 = 98.49%	27.56-1.99USAF-3.93NAVY+4.58RSAM-.90TLAM-.76PAT-.642MR+.173ATCM+.06HELO-1.76NAVY*RSAM-.869USAF*RSAM+.491USAF*NAVY+.321MR*HELO+.499NAVY^2+1.07USAF^2+.447TLAM-3.09RSAM^2
NEA Red Ground ED loss Adj R^2 = 60.92%	2.705+.180HELO-.0415MR+.382ATCM+.034NAVY+.015ARM+.019JSOW+.007USAF+.017ARTY+.002RSAM-.015PAT+.015SCUD+.042MR*HELO+.034MR*ARM+.023ARTY*RSAM+.033HELO*USAF .037MR*USAF-.017ATCM*USAF-.025HELO*JSOW+.021PAT*HELO-.019SCUD*HELO-.126HELO^2-.059MR^2
NEA US Ground ED loss Adj R^2 = 73.64%	.094+.040MR-.036HELO-.009ATCM-.008NAVY+.008ARTY-.006PAT-.006ARM-.016MR*HELO-.008MR*ATCM-.006MR*USAF-.013MR^2+005HELO^2
NEA Ally Ground ED loss Adj R^2 = 64.86%	1.32-.110HELO-.070ARM-.042ATCM-.036USAF-.027NAVY-.019PAT-.019ARTY+.008MR-.015INF-064MR*HELO-.052MR*ARM+.028ARM*HELO-.024MR*ATCM-.015MR*NAVY-.014MR*ARTY+.032HELO^2+.027ARM^2

SWA	*Model (With coded variables)*
SWA Halt Max % **Adj R^2 = 93.59%**	.8197+.147MR-.149HELO -.017ARM-.049ATCM-.028USAF+.003JSOW- .008ARTY-.010NAVY-.008INF-.004PAT+.004 SCUD-.028MR*HELO-.010MR*ARM+.010MR*USAF+.009MR*ATCM-.006HELO*JSOW- .007ARM*ARTY+.009ARM*HELO-.014HELO*ATCM+.009PAT*TLAM-.008SCUD*PAT-.065MR^2+.027HELO^2-.009JSOW^2-.012ATCM^2
SWA Halt Time **Adj R^2 = 86.64%**	6.35-1.26HELO-.607MR-.418ATCM-.252USAF .158ARM-.093NAVY+.062JSOW+.072INF+.620MR*HELO-.193ARM*HELO .165MR*USAF+.136MR*ARM .102MR*ATCM .105JSOW*USAF-.079MR*JSOW-.091HELO*ATCM-.083INF*HELO+.178HELO^2
SWA Red AC loss due to AA **Adj R^2 = 94.38%**	30.26-3.92PAT+3.32NAVY-3.13TLAM-2.55USAF+.536RSAM+.231SCUD+.758PAT*USAF-.620TLAM*RSAM-.610USAF*NAVY-.315TLAM*USAF+2.98TLAM^2+1.59PAT^2+.427USAF^2
SWA Red AC loss due to SAM **Adj R^2 = 93.97%**	41.22+11.63PAT-5.82USAF-1.46TLAM+.585SCUD-.076HELO-2.60PAT*TLAM-.641SCUD*USAF-.057SCUD*HELO+.461MR*PAT-.453MR*ATCM -.479MR*HELO 4.10USAF^2-2.93PAT^2+1.31TLAM^2
SWA Red AC loss due to other **Adj R^2 = 91.23%**	116.54+18.44USAF-6.86HELO-4.63TLAM-3.16MR-2.29ATCM-1.91PAT-1.16SCUD+1.608RSAM+3.37MR*HELO+2.24HELO*RSAM+1.69SCUD*USAF-1.47PAT*USAF+1.04MR*ATCM+1.17HELO*TLAM+1.14TLAM*RSAM-.881HELO*USAF-8.2USAF^2+4.53TLAM^2 +3.35RSAM^2+1.62HELO^2
SWA USAF AC loss due to AA **Adj R^2 = 89.22%**	8.07+1.05USAF-.198SCUD-.278TLAM+.091RSAM-.488PAT-.224NAVY- .368PAT*USAF+.222SCUD*USAF-.384TLAM*USAF-.123PAT*TLAM-.106TLAM*RSAM+.102USAF*RSAM-.120USAF*NAVY+.195SCUD*PAT+.121PAT*NAVY-1.403.USAF^2+.278TLAM^2+.247PAT^2
SWA USAF AC loss due to SAM **Adj R^2 = 99.09%**	16.06+4.67USAF-2.30NAVY+3.31RSAM-.154SCUD+.148PAT-1.37NAVY*RSAM+.752USAF*RSAM-.767USAF*NAVY-2.04RSAM^2+.549NAVY^2-.580USAF^2
SWA USAF AC loss due to other **Adj R^2 = 96.75%**	14.96-8.51PAT+8.14SCUD+1.20USAF-1.08MR+.274ARM-.737ATCM -2.17HELO+.734RSAM-4.27SCUD*PAT-.529PAT*USAF+.737SCUD*USAF-.503MR*SCUD-.469ARM*HELO+.593MR*PAT+1.31MR*HELO+.969PAT*HELO-.966SCUD*HELO-.458SCUD*ATCM+.409PAT*ATCM+.346USAF*RSAM+.617HELO*RSAM+.358SCUD*RSAM+.682RSAM^{2+}1.34PAT^2+.909HELO^2-.903USAF^2
SWA US NAC loss due to AA **Adj R^2 = 98.35%**	.788+.006MR+.566NAVY-.147USAF-.102TLAM-.103PAT+.014HELO+.009RSAM-.092USAF*NAVY-.064TLAM*NAVY-.058PAT*NAVY+.037PAT*USAF-.016MR*HELO+.011USAF*RSAM+.093TLAM^2 +.071USAF^2-.040NAVY^2+ .034PAT^2+.018HELO^2+.016MR^2
SWA US NAC loss due to SAM **Adj R^2 = 99.21%**	16.62+5.53NAVY+3.33RSAM-1.14USAF-.703USAF*RSAM+.598NAVY*RSAM-.470USAF*NAVY-2.120RSAM^2-.926NAVY^2+.313USAF^2
SWA Ally AC loss **Adj R^2 = 97.59%**	22.75-2.41USAF-4.50NAVY+4.01RSAM-.209TLAM-.215PAT-.521MR+.512HELO-1.76NAVY*RSAM-.709USAF*RSAM+.457USAF*NAVY+.325MR*NAVY-.400MR*RSAM+.192MR*USAF-.197HELO*USAF-.268HELO*NAVY+1.12NAVY^2+1.23USAF^2-2.87RSAM^2
SWA Red Ground ED loss **Adj R^2 = 67.48%**	2.51+.277HELO+.120RSAM+.127ATCM+.042USAF-.051MR+.039ARM+.154MR*HELO+.149HELO*RSAM+.076ATCM*RSAM+.066MR*ATCM-.054ARM*HELO-.048HELO*USAF+.039USAF*RSAM+.117RSAM^2
SWA US Ground ED loss **Adj R^2 = 65.78%**	.0296-.0232HELO+.0096MR-.0080USAF-.0074ATCM-.0039PAT-.0029NAVY .0027HELO*USAF+.0032PAT*USAF+.0107HELO^2
SWA Ally Ground ED loss **Adj R^2 = 52.13%**	.8375-.039HELO+.026MR-.019ATCM-.009USAF-.0022ARM-.0008TLAM+.042MR*HELO+.017MR*ATCM+.010MR*USAF-.010ARM*TLAM-.025MR^2

Appendix C

ACRONYMS AND ABBREVIATIONS

AAD	average absolute difference
APC	armored personnel carriers
AWACS	Airborne Warning and Control System
C4ISR	command, control, communication, computers, intelligence, surveillance, and reconnaissance
CVBG	aircraft carrier battle group
ED	effective divisions
GAMS	General Algebraic Modeling System
GCAM	General Campaign Analysis Model
GCC	Gulf Cooperation Council
IFV	Infantry Fighting Vehicles
JHU/APL	The Johns Hopkins University Applied Physics Laboratory
JICM	Joint Integrated Contingency Model
JSOW	Joint Standoff Weapon
JSTARS	Joint Surveillance Target Attack Radar System
JWARS	Joint Warfare System
MAD	maximum absolute difference
MOE	measures of effectiveness
MOO	measures of outcome
mph	miles per hour
MSE	mean square error

NEA	Northeast Asia
NLP	nonlinear programming
OPSIT	operational situation
RSM	response surface methodology
SAM	surface-to-air missile
SME	subject matter expert
SWA	Southwest Asia
TLAM	Tomahawk land-attack missile
USAF	U.S. Air Force
USN	U.S. Navy